Abstract

From domestic terror attacks orchestrated by homegrown nationalist groups to international attacks coordinated by some of the largest global terror networks in the world, the rise of terrorism has fueled significant interest in understanding terrorism and its spread. Beyond the real threats that terrorism poses to institutions and individuals alike, understanding how terrorism spreads and how individuals become more radicalized is of significant interest in computational social science study. In this study, I attempt to create an agent-based model (AGM) that tracks how terrorist events and influence from radicalizers alter an agent's propensity to be radicalized; these issue findings that computationally confirm perceptions about terrorism and how radicalization works in closed-off systems.

I.Background

This model was created with the intention of simulating the change in an individual/agent's propensity to become radicalized (computed through a given score) based on certain distributions and probabilities of terrorist events and radicalizer influence. There are a number of reasons, both theoretical and practical, for attempting to create a computational model/simulation of radicalization propensity. Practically speaking, the rise of international terrorist incidents in the last two decades is concerning; Awan (2017) describes how — counter to previous terrorist recruitment models which required extensive in-person contact with an agent, organizations like ISIS have been able to flip models of radicalizing and recruiting on their head by using online social networks (OSNs) such as Twitter and Facebook as vehicles of spreading propaganda, violent videos, and other messaging to a new variety of recruits through cyber-jihadism. More than just new modes of radicalizing via social media, domestic terrorist incidents are rising. Although Williams (2018) discusses that most domestic terror tends to be lone-wolf terror, even in the absence of radicalizer influence, there tend to be events that crystallize into an increased propensity to commit a terrorist act. While this model does not attempt to model the semantics of human behavior that might lead an individual agent to commit a terror attack — which even the most complex and systematic machine-learning models are attempting to do — it does attempt to model how a change in the distribution of events or a change in radicalizer contact influence can cause differences in an individual's propensity to be radicalized. Theoretically, the emergent social conditions that come from potential recruits of terrorist organizations or the unique circumstance that drive radicalization are little understood despite ongoing efforts to discern such factors. Therefore, the creation of a computation agent-based model is fitting: it is another attempt to model the exogenous factors that drive individuals in the direction of terrorism.

There are a few different domains that this model hopes to address. While it is intuitive that the influence from a radicalizing agent would lead to an increased propensity to be radicalized (or a higher radicalization score as I illustrate in my model), a finding that is extensively backed by literature such as in Smith (2018) when she describes how contact with extremist belief systems in one's social networks of friends and family increases their chance of self-identifying with an extreme belief, it is less intuitive how occurrences of terrorist events are likely to work in altering one's extreme beliefs. I turn to literature to gain a better understanding of how this might play out. Gomez et al. (2021) highlight how people become 'radicalized' because they usually experience either 'compliance' or 'internalization' where compliance is when individuals are forced to join an organization and 'internalization' is when individuals experience a convergence between their own identity and the group-identity. However, in order to experience convergence in its purest form, Trip et al. (2019) suggests that an individual who is on the path towards being radicalized has to be willing to conform to multiple 'absolutistic demands', particularly demands of the self, of others, and of the world. Because the conditions towards converging with a group are so complicated in non-isolated systems and because of the variegated psychological systems at play in determining whether an individual grows more attached or disassociates with their group after an attack, no simple computational model can uniformly describe the change in one's propensity based on terrorist attacks. I contend that repeated instances of global terrorist attacks and their existential danger to nations, institutions, and individuals is of the utmost import in computational social science. Modeling the change in radicalization scores in a controlled setting would be productive in discerning how events, given key assumptions, can alter the dynamics of one's radicalization propensity.

II.Existing Models and the Gap

There have been myriad efforts at constructing agent-based models (ABMs) that work to simulate radicalization dynamics and behavior. Operationally, though, since the mechanism that drives radicalization are both psychological, such as feelings of isolation and the need to find community, and environmental, closely related to one's political circumstances and who they are connected to in their network, there remains a great deal of variety in ABMs as they attempt to model radicalization. Doran (2005) created one of the principal ABMs to model guerrilla warfare, using a historical case study to determine the built-in components in the function the model relies upon. However, in his model, the radicalizing agents are either 'recruited' or they are initialized at model start. While computationally sound, his model is both specific to the context of guerilla-warfare conditions and lacks discussion of how radicalization emerges out of social conditions. Another well-documented ABM is that of Epstein (2002) who attempted to model civil violence created a function of hardship and the legitimacy of imposed hardship in order to equal grievance. The model admirably attempts to mathematically dogmatize instances where an individual would take action against their government. The issue with this lies in its randomly created exogenous influences that allow for differences in the function outputs without an adequate basis in social theory that prompts an understanding of why said output values are appropriate (Cioffi-Revilla and Harrison, 2011). The ongoing issue in modeling lies in either the avoidance of psychological influence in radicalization schemas or the hyperspecific instances in which models can be applied such as civil violence against the state or guerilla warfare.

While numerous ABMs from the literature surrounding radicalization map out the changes to initial networks or agents differently, my model aims to be foundational in terms of modeling psychosocial changes among agents who have not been radicalized. Rather than opt to use a network that would introduce a whole host of factors into the model, I chose to iterate through exogenous conditions that attempt to have some of the psychological underpinnings of radicalization built in while also highlighting different case studies.

III.Model Design and Assumptions of Model

III. I Assumptions

Our model had some foundational assumptions built in that operationally enabled its use. What the model lacks in mathematical complexity, it retains in foundational use. Rather than choose to create the model as a network, I created radicalization scores that were assigned to individuals in a list. For the sake of modeling, I treated said list as a closed system that featured positive radicalization influence from radicalizers in the network and negative radicalization influence from local Terrorist Events. Although radicalization rarely operates in a closed ecosystem, treating it as such allows for more attention to be paid to how scores might change over time if exogenous changes occurred that incorporated social factors.

1. Influence from radicalizers are likely to increase one's propensity to become radicalized.
2. There are certain events that can decrease one's propensity to become radicalized; in our model, these are local terrorist attacks — which more effectively decrease the propensity to become radicalized for those who are less radicalized and less effectively decrease the propensity to become radicalized for those who are more radicalized.
3. Events and Radicalizers are not all the same — stronger Events tend to decrease scores more and stronger Radicalizers tend to increase scores more. The converse is true with weaker Events/Radicalizers.
4. There exists some threshold value above which people become radicalized.

While the fourth assumption is not instrumental to model design, the rest of our assumptions guided the creation of our model and allowed us to compute the change in radicalization over time.

III.II Design of the Model and Mathematical Set-Up

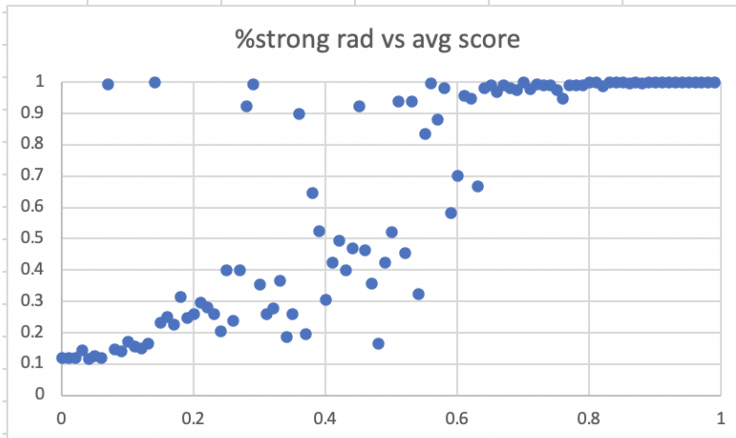
Fundamentally speaking, our model observes changes in values to a list [] radicalizePoteential. It randomly assigns scores to agents in the model between bounds 0 and 1, which is done through the assignScores function.

Following the initialization of the list and all the corresponding randomly generated scores between 0 and 1, the model then features four different functions defSimulateStrongEvent, defSimulateStrongRadicalizer, defSimulateWeakEvent, and defSimulateWeakRadicalizer. Ultimately, though, the defSimulateRounds function is what determines the exogenous influence that alters the initialScores and turns them into finalScores.

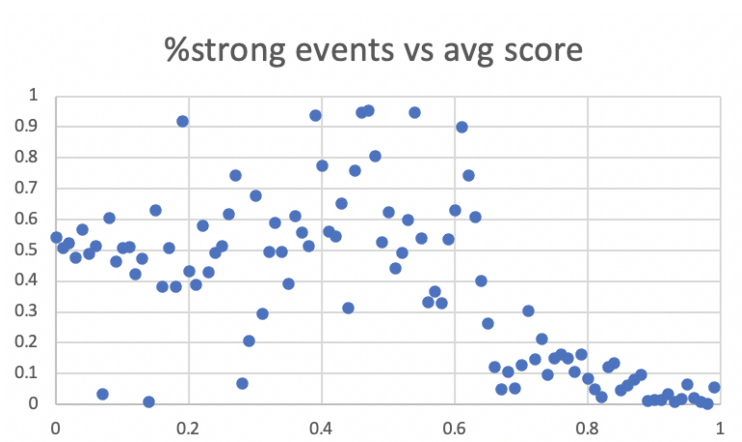
In the case of user input, which the model has and can be seen in the Appendix, the model calculates the number of events of type Strong and Weak by multiplying the number of events the User selected with

IV. Results

The results are definitely interesting but could be due in part to the way the model was designed. First and foremost, after iterating through the Probability of Strong Radicalizers by 0.5 from 0% to 100%, the results reveal a clear positive relationship between the scores of agents in the model at the end. That is, as the % of strong Radicalizers increases, the final Scores also linearly increase.



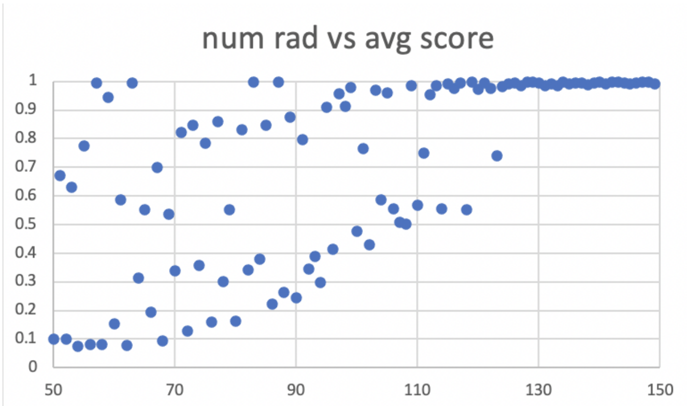
The same is true with the graph inputting differences in the % of Strong Events and final scores: there appears to be a clear negative linear relationship.

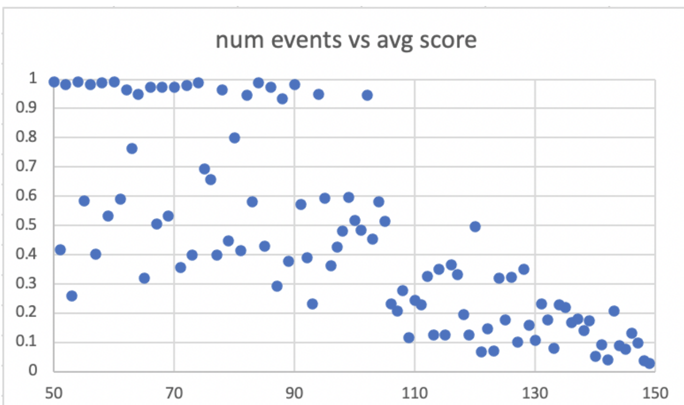


I also tracked variance in the number of Radicalizers present and the average final score of all the agents in the list along with the number of Events and differences in the average final Score which are displayed in the corresponding figures. The results suggest that as the number of events increases, the average final Score decreased and as the number of Radicalizers increases, the average final Score correspondingly increased.

V. Discussion

The analysis reveals that the model functionally behaves as one would expect, albeit in a rudimentary way. The basis of the model is to map changes in the agents' scores based on exogenous conditions





such as Events and Radicalizers. As expected, as the probabilistic chance that the model contains mostly strong Events increases, the model features higher score reductions across the board; the random chance of having weakerEvents dwarfed the influence of strong radicalizer %, which is held stable during data collection is also overshadowed by Event %. On the other end of the spectrum, it appears as if when strong radicalizer % varies and strong Event % is fixed, the results tend towards higher scores.

More interesting, though, are the latter two graphs which, when iterating between 50 and 150 events and radicalizers, still show a declining pattern for more events and an increasing pattern for more radicalizers.